TWO-DIMENSIONAL HIDDEN MARKOV MODELS IN ROAD SIGNS RECOGNITION

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Abstract

This paper presents an automatic road sign recognition system. The system bases on two-dimensional hidden Markov models. First, a study of the existing road sign recognition research is presented. In this study, the issues associated with automatic road sign recognition are described, the existing methods developed to tackle the road sign recognition problem are reviewed, and a comparison of the features of these methods is given. Second, the created road sign recognition system is described. The system is able to recognize the road signs, which was detected earlier. The system makes use of two dimensional discrete wavelet transform for features extraction of road signs. In recognition process system bases on two dimensional hidden Markov models. The experimental results demonstrate that the system is able to achieving an average recognition rate of 83% using the two-dimensional hidden Markov models and the wavelet transform.
Keywords: two dimensional hidden Markov model, road sign recognition, image recognition, image processing.

1 Introduction

Lots of research in the field of automatic road sign detection and recognition systems has been done for last thirty years. The main object of such systems is to warn them of presence of road signs in different ways, because drivers may not notice the presence of them. It is important to note to some of the common problems that are appear in road signs detection. The main problem to be overcome is caused by the variable lighting conditions of a scene in a natural environment and the possible rotation of the signs. An automatic system should be able to detect signs in different condition and position [6, 15]. The first paper in the field of road sign recognition appears in Japan in 1984. Since then, great amount of methods have been developed to locate and identify road signs. A road sign is individual in its colour, shape, and appearance. Most of the existing methods use the combination of these properties to determine the meaning of road sign content [16]. Detection of road sign are mainly based on colour criteria [6] or shape information [20]. As a result, the colour space plays an lead role. The popular RGB color space are used in [3]. However, the RGB space is not optimized for problems of road signs recognition, because it is sensitive to lighting conditions changes [5]. Colour spaces that are more independent to such changes is HSV, and it is used in [13]. They applied a threshold over a hue, saturation, value representation of the image to find regions with a road sign. After a road sign has been detected, it should be recognized from a large set of possible patterns using some of classification method. The symbol of detected sign must be suitably represented for a specific classification method that is usually done by extracting some features from the image. Examples of features extracting techniques are histograms [22] and wavelets [8]. After the choosing of appropriate features, many classification methods have been proposed, different kinds of neural networks [22, 8, 17], SVM [13] or hidden Markov model [7]. This paper presents an automatic road sign recognition system with following properties:(i) the system uses two dimensional wavelet transform of second level decomposition for features extraction, (ii) the classification module bases on two dimensional hidden Markov models, which work with two dimensional data.

Hidden Markov models (HMM) are widely apply in data classification. They are used in speech recognition, character recognition, biological sequence analysis, financial data processing, texture analysis, face recognition, etc. This widely application of HMM is result of its effectiveness. An extension of the HMM to work on two-dimensional data is 2D HMM. A 2D HMM can be regarded as a combination of one state matrix and one observation matrix, where transition between states take place according to a 2D Markovian probability and each observation is generated independently by the corresponding state at the same matrix position. It was noted that the complexity of estimating the parameters of a 2D HMMs or using them to perform maximum a posteriori classification is exponential in the size of data. Similar to 1D HMM, the most important thing for 2D HMMs is also to solve the three basic problems, namely, probability evolution, optimal state matrix and parameters estimation.

When we process one-dimensional data, we have good tools and solution for this. Unfortunately, this is unpractical in image processing, because the images are two-dimensional. When you convert an image from 2D to 1D , you lose some information. So, if we process two-dimensional data, we should apply two-dimensional HMM, and this 2D HMM should works with 2D data. One of solutions is pseudo 2D HMM [2, 23, 11]. This model is extension of classic 1D HMM. There are super-states, which mask one-dimensional hidden Markov models (Fig. 1). Linear model is the topology of superstates, where only self transition and transition to the following superstate are possible. Inside the superstates there are linear 1D HMM. The state sequences in the rows are independent of the state sequences of neighboring rows. Additional, input data are divided to the vector. So, we have 1D model with 1D data in practise.

Other approach to image processing use two-dimensional data present in works [12] and [9]. The solutions base on Markov Random Fields (MRF) give good results for classification and segmentation, but not in pattern recognition. Interesting results showed in paper [24]. This article presents analytic solution and proof of correctness two-dimensional HMM. But this 2D HMM is similar to MRF, works with one-dimensional data and can be apply only for left-right type of HMM. This article presents real solution for 2D problem in HMM. There is show true 2D HMM which processes 2D data.

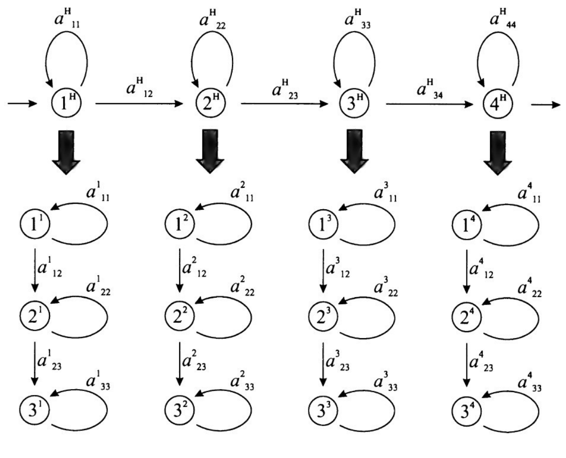

Figure 1: Pseudo 2D HMM [2].

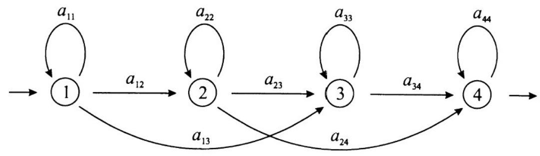

Figure 2: One-dimensional HMM.

2 Classic 1D HMM

HMM is a double stochastic process with underlying stochastic process that is not observable (hidden), but can be observed through another set of stochastic processes that produce a sequence of observation [18]. Let $O = \{O_1, .., O_T\}$ be the sequence of observation of feature vectors, where T is the total number of feature vectors in the sequence. The statistical parameters of the model may be defined as follows [10]:

- The number of states of the model, N
- The number of symbols M
- The transition probabilities of the underlying Markov chain, $A = \{a_{ij}\}, 1 \leq i, j \leq N$, where a_{ij} is the probability of transition from state i to state j
- The observation probabilities, $B = \{b_{jm})\} \quad 1 \leq j \leq N, 1 \leq m \leq M$ which represents the probability of gnerate the m_{th} symbol in the j_{th} state.
- The initial probability vector, $\Pi = \{\pi_i\} \quad 1 \leq i \leq N$.

Hence, the HMM requires three probability measures to be defined,A, B, Π and the notation $\lambda = (A, B, \Pi)$ is often used to indicate the set of parameters of the model. In the proposed method, one model is made for each part of the face. The parameters of the model are generated at random at the beginning. Then they are estimated with Baum-Welch algorithm, which is based on the forward-backward algorithm. The forward algorithm calculates the coefficient $\alpha_t(i)$ (probability of observing the partial sequence $(o_1, , o_t)$ such that state q_t is i). The backward algorithm calculates the coefficient $\beta_t(i)$ (probability of observing the partial sequence $(o_{t+1}, , o_T)$ such that state q_t is i). The Baum-Welch algorithm, which computes the λ, can be described as follows [10]:

1. Let initial model be λ_0
2. Compute new λ based on λ_0 and observation O
3. If $log(P(O|\lambda) - log(P(O)|\lambda_0) < DELTA$ stop
4. Else set $\lambda \rightarrow \lambda_0$ and go to step 2.

The parameters of new model λ, based on λ_0 and observation O, are estimated from equation of Baum-Welch algorithm [18], and then are recorded to the database.

2.1 Three basic problems

There are three fundamental problems of interest that must be solved for HMM to be useful in some applications. These problems are the following:

1. Given observation $O = (o_1, o_2, , o_T)$ and model $\lambda = (A, B, \Pi)$, efficiently compute $P(O|\lambda)$
2. Given observation $O = (o_1, o_2, , o_T)$ and model λ find the optimal state sequence $q = (q_1, q_2, , q_T)$
3. Given observation $O = (o_1, o_2, , o_T)$, estimate model parameters $\lambda = (A, B, \Pi)$ that maximize $P(O|\lambda)$

To create a system of pattern recognition is necessary to solve the problem 1 and 3.

2.2 Solution to Problem 1

Solution for problem 1 is well know forward-backward algorithm [10].

Forward algorithm

- Define forward variable $\alpha_t(i)$ as:

$$\alpha_t(i) = P(o_1, o_2, , o_t, q_t = i|\lambda) \qquad (1)$$

- $\alpha_t(i)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i

Backward algorithm [10]

- Define backward variable $\beta_t(i)$ as:

$$\beta_t(i) = P(o_{t+1}, o_{t+2}, , o_T, q_t = i|\lambda) \qquad (2)$$

- $\beta_t(i)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i

2.3 Solution to Problem 3

Baum-Welch Algorithm [10]:

- Define $\xi(i, j)$ as the probability of being in state i at time t and in state j at time $t + 1$
$\xi(i, j) = \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{P(O|\lambda)}$

$$= \frac{\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)}{\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_t(i)a_{ij}b_j(o_{t+1})\beta_{t+1}(j)} \qquad (3)$$

- Define $\gamma(i)$ as the probability of being in state i at time t, given observation sequence.

$$\gamma_t(i) = \sum_{j=1}^{N}\xi_t(i, j) \qquad (4)$$

- $\sum_{t=1}^{T}\gamma_t(i)$ is the expected number of times state i is visited
- $\sum_{t=1}^{T-1}\xi_t(i, j)$ is the expected number of transition from state i to j

Update rules:

- $\bar{\pi}_i$ = expected frequency in state i at time $(t = 1) = \gamma_1(i)$
- $\bar{a}_{ij}$ = (expected number of transition from state i to state j)/(expected number of transitions from state i:

$$\bar{a}_{ij} = \frac{\sum_t \xi_t(i, j)}{\sum_t \gamma_t(i)} \qquad (5)$$

- $\bar{b_j}(k)$ = (expected number of times in state j and oserving symbol k)/(expected number of times in state j:

$$\bar{b}_j(k) = \frac{\sum_{t,o_t=k}\gamma_t(j)}{\sum_t \gamma_t(j)} \qquad (6)$$

3 2D HMM

In paper [24], Yujian proposed definitions and proofs of 2D HMM. He has presented several analytic formulae for solving the three basic problems of 2-D HMM. Solution to Problem

2 is usefull, and Viterbi algorithm can be easily adopted to image recognition with two dimensional input data. Unfortunetly, solution to problem 1 and 3 may be use only with one dimensional data -observation vector. Besides presented solutions are for Markov model type "left-right", and not ergodic. So, we present solution to problems 1 and 3 for two dimensional data, which is sufficient to build a image recognition system. The statistical parameters of the 2D model (Fig. 3):

- The number of states of the model N^2
- The number of data streams k_1 x $k_2 = K$
- The number of symbols M
- The transition probabilities of the underlying Markov chain, $A = \{a_{ijl}\}, 1 \le i,j \le N, 1 \le l \le N^2$, where a_{ij} is the probability of transition from state ij to state l
- The observation probabilities, $B = \{b_{ijm})\}, 1 \le i,j \le N, 1 \le m \le M$ which represents the probability of gnerate the m_{th} symbol in the ij_{th} state.
- The initial probability, $\Pi = \{\pi_{ijk}\}, 1 \le i,j \le N, 1 \le k \le K$.
- Oservation sequance $O = \{o_t\}, 1 \le t \le T, o_t$ is square matrix simply observation with size k_1 x $k_2 = K$

3.1 Solution to 2D Problem 1

Forward Algorithm

- Define forward variable $\alpha_t(i,j,k)$ as:

$$\alpha_t(i,j,k) = P(o_1, o_2, , o_t, q_t = ij|\lambda) \quad (7)$$

- $\alpha_t(i,j,k)$ is the probability of observing the partial sequence $(o_1, o_2, , o_t)$ such that the the state q_t is i,j for each k_{th} strem of data

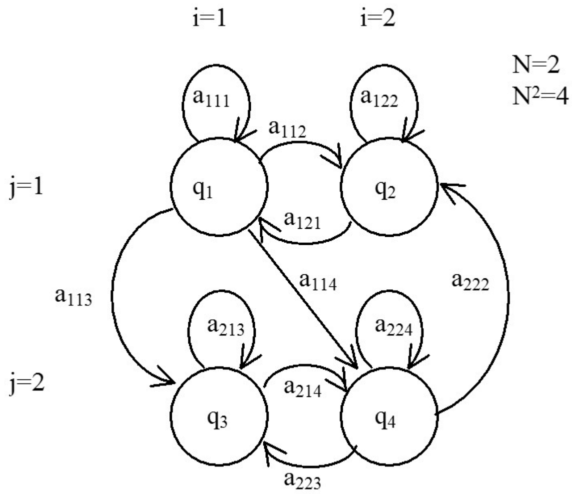

Figure 3: Two-dimensional ergodic HMM.

- Induction
  1. Initialization:

$$\alpha_1(i,j,k) = \pi_{ijk} b_{ij}(o_1) \quad (8)$$

  2. Induction:

$$\alpha_{t+1}(i,j,k) = \left[\sum_{l=1}^{N} \alpha_t(i,j,k) a_{ijl}\right] b_{ij}(o_{t+1}) \quad (9)$$

  3. Termination:

$$P(O|\lambda) = \sum_{t=1}^{T}\sum_{k=1}^{K} \alpha_T(i,j,k) \quad (10)$$

3.2 Solution to 2D Problem 3

Parameters reestimation Algorithm:

- Define $\xi(i,j,l)$ as the probability of being in state ij at time t and in state l at time $t+1$ for each k_{th} strem of data $\xi_t(i,j,l) = \frac{\alpha_t(i,j,k) a_{ijl} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)}{P(O|\lambda)} =$

$$\frac{\alpha_t(i,j,k) a_{ij} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)}{\sum_{k=1}^{K}\sum_{l=1}^{N^2} \alpha_t(i,j,k) a_{ijl} b_{ij}(o_{t+1}) \beta_{t+1}(i,j,k)} \quad (11)$$

- Define $\gamma(i,j)$ as the probability of being in state i,j at time t, given observation sequence.

$$\gamma_t(i,j) = \sum_{l=1}^{N^2} \xi_t(i,j,l) \qquad (12)$$

- $\sum_{t=1}^{T} \gamma_t(i,j)$ is the expected number of times state ij is visited
- $\sum_{t=1}^{T-1} \xi_t(i,j,l)$ is the expected number of transition from state ij to l

Update rules:

- $\pi_i\bar{j}k$ = expected frequency in state i,j at time $(t=1) = \gamma_1(i,j)$
- $\bar{a}_{ij}$ = (expected number of transition from state i,j to state l)/(expected number of transitions from state i,j:

$$\bar{a}_{ijl} = \frac{\sum_t \xi_t(i,j,l)}{\sum_t \gamma_t(i,j)} \qquad (13)$$

- $\bar{b_{ij}}(k)$ = (expected number of times in state j and oserving symbol k)/(expected number of times in state j:

$$\bar{b}_{ij}(k) = \frac{\sum_{t,o_t=k} \gamma_t(i,j)}{\sum_t \gamma_t(i,j)} \qquad (14)$$

4 Experiments

The road signs image database *German Traffic Sign Benchmark* was used in experimenting [1]. As authors wrote [21], the set contains images of more than 1700 traffic sign instances. The size of the traffic signs varies between 1515 and 222193 pixels. The images contain 10% margin (at least 5 pixels) around the traffic sign to allow for the usage of edge detectors. The original size and location of the traffic sign within the image (region of interest, ROI) is preserved in the provided annotations. The images are not necessarily square. Fig. 4 shows the distribution of traffic sign sizes, taking into account the larger of both dimensions of the traffic sign ROI.

Figure 4: Random representatives of the traffic sign in the GTSRB dataset [1].

Table 1: Comparison of recognition rate

Method	Recognition rate [%]
ESOM [14]	84
HMM [7]	49
1D HMM[our]	81
2D HMM[our]	83

In order to verify the method has been selected fifty objects. Three images for learning and three for testing has been chosen for each object. The 2D HMM has been implemented with parameters $N = 4, N^2 = 16, K = 16, M = 25$. The parameters of HMM was selcted randomly and estimated by modify Baum-Welch algorithm (sec. 4.2). Wavelet transform has been chosen as features extraction technigue. Table 1 presents The results of experiments.

5 Conclusion

In this paper, the new conception about road sign recognition with two-dimensional hidden Markov models was presented. We show solutions of principle problems for ergodic 2D HMM, which may be applied for 2D data. Recognition rate of the method is 83%, which is better than 1D HMM. Furthermore, the advantage of this approach is that there is no need to convert the input two-dimensional image on a one-dimensional data and we do not lose the information. The obtained results are satisfactory in comparison to other method and proposed method can be the alternative solution to the others.

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